

Merge-of-Thought Distillation

Zhanming Shen^{♣*}, Zeyu Qin^{♣*}, Zenan Huang[♣], Hao Chen^{♣♣},
Jiaqi Hu^{♣♣}, Yihong Zhuang[♣], Guoshan Lu[♣], Gang Chen[♣], Junbo Zhao^{♣♣†}
[♣]Zhejiang University [♣]Inclusion AI, Ant Group
 {z.shen, j.zhao}@zju.edu.cn

Abstract

Efficient reasoning distillation for long chain-of-thought (CoT) models is increasingly constrained by the assumption of a single oracle teacher, despite practical availability of multiple candidate teachers and growing CoT corpora. We revisit teacher selection and observe that different students have different “best teachers,” and even for the same student the best teacher can vary across datasets. Therefore, to unify multiple teachers’ reasoning abilities into student with overcoming conflicts among various teachers’ supervision, we propose **Merge-of-Thought Distillation (MoT)**, a lightweight framework that alternates between teacher-specific supervised fine-tuning branches and weight-space merging of the resulting student variants. On competition math benchmarks, using only about **200** high-quality CoT samples, applying MoT to a **Qwen3-14B** student surpasses strong models including **DEEPSEEK-R1**, **QWEN3-30B-A3B**, **QWEN3-32B**, and **OPENAI-O1**, demonstrating substantial gains. Besides, MoT consistently outperforms the best single-teacher distillation and the naive multi-teacher union, raises the performance ceiling while mitigating overfitting, and shows robustness to distribution-shifted and peer-level teachers. Moreover, MoT reduces catastrophic forgetting, improves general reasoning beyond mathematics and even cultivates a better teacher, indicating that consensus-filtered reasoning features transfer broadly. These results position MoT as a simple, scalable route to efficiently distilling long CoT capabilities from diverse teachers into compact students.

1 Introduction

As large language models (LLMs) with long chain-of-thought (CoT) capabilities continue to emerge Jaech et al. [2024], Yang et al. [2025a], Guo et al. [2025], reasoning distillation is becoming the key pathway for converting expensive reasoning ability into deployable efficiency. Compared with imitating only final answers, directly supervising the reasoning trajectory enables a smaller student model to learn multi-step solution procedures Luo et al. [2025b], Qin et al. [2025], Guo et al. [2025].

Building on this, the research focus is naturally shifting from “stacking quantity” to “improving quality and supporting mechanisms”: on the one hand, Muennighoff et al. [2025] performs SFT on only 1,000 teacher-distilled samples and shows reasoning gains with test-time compute; on the other hand, Ye et al. [2025] shows that when pretraining already embeds rich mathematical knowledge, a few hundred carefully curated examples can effectively elicit complex reasoning. Overall, these advances jointly emphasize that **efficient distillation of long CoT reasoning** is a scalable route to high-accuracy small models.

However, real-world production rarely feature a “single oracle teacher.” We often have **multiple candidate teacher LLMs** and a growing pool of distilled CoT data, giving rise to a basic question:

* Equal Contribution.

† Corresponding Author.

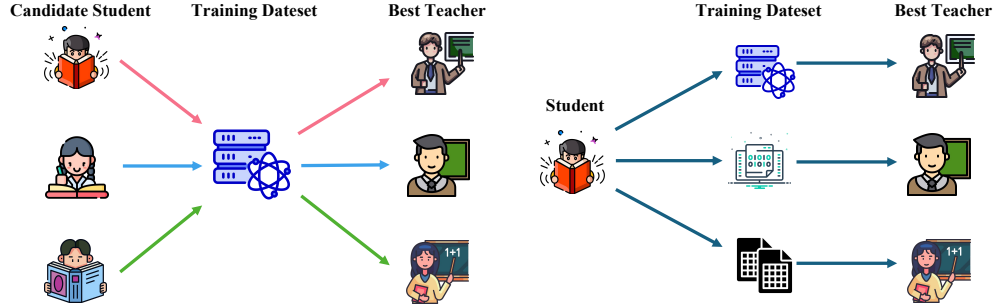


Figure 1: Teacher choice is not universal. Left: different students have different “best teachers”; right: even for the same student the best teacher can vary across datasets. This observation is empirically confirmed in Table 5, which reports the best teacher for each base model and dataset, showing that the top teacher depends on both the student and the dataset.

given a student model, how should we pick the most suitable teacher? Empirically, teacher choice matters—the teacher can imprint a recognizable “style signature” on the student Chen et al. [2025b]; mismatches between teacher and student can weaken the transfer of long CoT skills Wu et al. [2025b]. As illustrated in Figure 1, our observations are consistent: different students have different “best teachers,” and even for the same student the best teacher can vary across datasets. Such phenomena challenge the naive assumption that “a bigger/stronger teacher is necessarily better,” prompting us to consider: rather than *centering on* a single teacher and *taking cost on* teacher selection, maybe we should *transfer across* multiple teachers.

A natural follow-up question is: **can we fuse the strengths of multiple teachers**—integrating diverse reasoning styles and complementary skills into a single student to achieve stronger performance? Recent studies have shown that long CoTs, due to excessive length and redundant steps, tend to accumulate more noise and irrelevant content Luo et al. [2025a], Zhang et al. [2025], Li et al. [2025b]. It is unclear whether, in mixed-teacher long-CoT distillation, such noise is amplified through interactions, and how to suppress idiosyncratic noise while preserving the consensus structure. These trends suggest that *diversity of teachers and reasoning paths* is an asset—provided we can overcome conflicts among various teachers’ supervision.

Model merging has already demonstrated that merging can help models fit to different data distributions and is widely applied to joint training across diverse domains and tasks Yu et al. [2024b], Zhou et al. [2024], Yadav et al. [2024]. Inspired by these advantages, we aim to leverage *model merging* to overcome conflicts among various teachers’ supervision and, through continuous merge-and-training iterations, unify different teachers’ reasoning abilities and ultimately converge to a consensus reasoning landscape.

To this end, we propose **Merge-of-Thought Distillation (MoT)**: a lightweight framework that **alternates** between (i) **teacher-specific branch SFT** and (ii) **weight-space merging of student variants**. Intuitively, branch SFT internalizes each teacher’s reasoning style in the student; the subsequent parameter-space merge then **distills consensus**—retaining features reinforced across teachers while suppressing individual accidents and quirks. After multiple iterations, the student progressively condenses into a **merged student** that reflects multi-teacher consensus reasoning.

Main findings. We present, to our knowledge, the **first systematic study of multi-teacher long-chain CoT co-distillation**.

1. We conduct the revisiting analysis of teacher selection under Long CoT distillation setting and find that there is **no single "best teacher"** consistently dominant across students or datasets.
2. Rather than taking cost on teacher selection, We propose a novel distillation method, **Merge-of-Thought Distillation (MoT)**, to unify multiple teachers’ reasoning abilities into student with overcoming conflicts among various teachers’ supervision.
3. On competition math benchmarks, using only about **200** high-quality CoT samples, applying MoT to a **Qwen3-14B** student surpasses strong models including **DEEPSEEK-R1**,

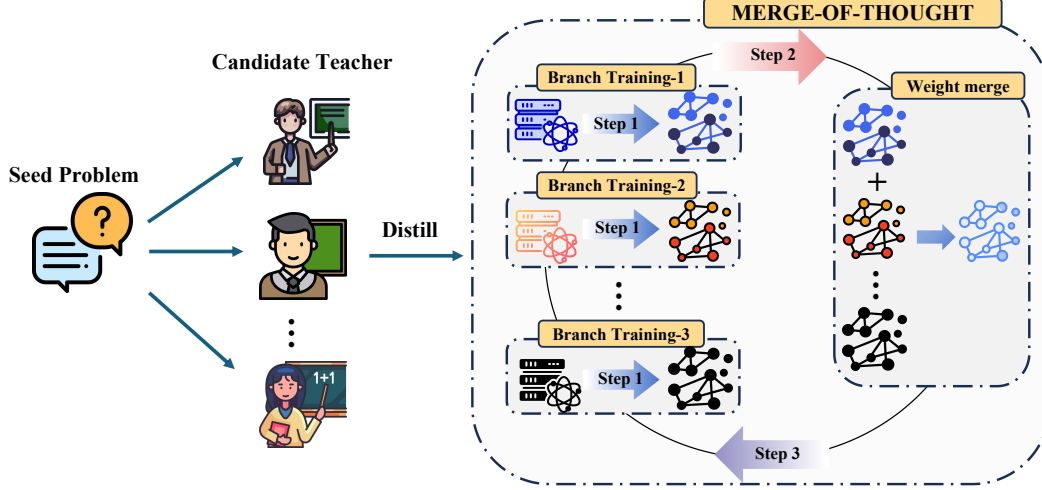


Figure 2: Workflow of Merge-of-Thought Distillation (MoT). After the candidate teachers generate the teacher-specific distillation dataset based on the seed problem, the system enters the iterative MOT algorithm process. In each round t , we perform three steps: **Step 1 (branch training)**: initialize K branches from the current merged student and train each on its teacher-specific distillation dataset $\mathcal{D}^{(k)}$ (Eq. 1); **Step 2 (weight merge)**: average the branch parameters in weight space to obtain the aggregated model $\theta^{(t)}$ (Eq. 2); **Step 3 (next-round initialization)**: use $\theta^{(t)}$ as the base initialization for round $t+1$.

QWEN3-30B-A3B, QWEN3-32B, and OPENAI-O1, demonstrating substantial gains. Besides, MoT distillation always outperforms **per-setting best single teacher distillation** and shows robustness to distribution-shifted and peer-level teachers.

4. MoT **mitigates catastrophic forgetting** and yields general reasoning improvements beyond mathematics, suggesting that consensus-filtered reasoning features possess broader transferability. Therefore, when the MoT-merged student model **serves as a teacher**, its downstream distillation effect is also **stronger**.

2 Related Work

Long Chain-of-Thought Distillation. Research on distilling long chains of thought (CoT) has progressed rapidly Wu et al. [2025b], Guo et al. [2025]. Early work Li et al. [2023] showed that even small models can benefit from teacher CoT prompting and highlighted the importance of using diverse teachers to obtain varied reasoning chains. *Skip-Thinking* partitions long reasoning into coherent segments and skips non-essential parts, improving efficiency and alleviating gradient over-smoothing Chen et al. [2025a]. Subsequent approaches like *DLCot* Luo et al. [2025b] and *KPOD* Feng et al. [2024] further segment and simplify CoTs, employ keypoint weighting, and use progressive distillation to focus on critical tokens and steps. Studies on the key factors of CoT distillation reveal that teacher diversity and rationale granularity often have a greater impact than raw teacher accuracy Chen et al. [2025b]. Recent works show that long-CoT capability can be bootstrapped with a handful of in-context examples Pang et al. [2025], distilled as summaries to improve long-context memory Ma et al. [2025], or integrated with vision reasoning using agent-based approaches Shi et al. [2024]. These findings underscore that long-CoT distillation not only requires carefully curated examples but also faces challenges such as **teacher selection**, **noise amplification** and **distillation efficiency**. Nevertheless, most existing methods focus on a **single teacher distillation**; our work instead extends this line of work by fusing multiple teachers’ reasoning abilities into a single student to achieve stronger performance.

Model Merging in LLMs. Model merging fuses the parameters of multiple trained models into a single model, which is distinct from output-level ensembles Yang et al. [2024], Tam et al. [2024]. Empirical studies show that merging tends to **balance performance** and safety better than mixing data

across tasks or languages Yang et al. [2025b], Yadav et al. [2024], Yu et al. [2024b], Jin et al.. More advanced techniques adapt merging to pre-trained models by disentangling weights into magnitude and direction Yu et al. [2024a]. Other approaches merge checkpoints during pre-training for faster convergence or use activation importance to retain critical parameters Li et al. [2025a], Nobari et al. [2025]. Model merging has also been applied to combine models with different reasoning strategies and to merge heterogeneous architectures Wu et al. [2025a], Zhang et al. [2024]. However, most existing work focuses on merging models specialised for different domains and tasks; by contrast, our approach merges student models distilled by different teachers **on the same dataset** to **unify their reasoning abilities** without conflicts among different teachers.

3 Method: Merge-of-Thought Distillation (MoT)

Our approach assumes access to a base language model, a small set of supervised problems with reference answers, and multiple teacher models that can produce chains-of-thought (CoTs). The core idea is to consolidate reasoning signals that are consistent across heterogeneous teacher rationales. MoT alternates between teacher-specific supervised fine-tuning (SFT) branches and weight-space merging, and is performed iteratively.

Concretely, MoT consists of two core steps repeated for multiple rounds:

1. *Branch training (teacher-specific SFT)*: For each teacher, fine-tune a branch of the student on that teacher’s rationales.
2. *Weight merge*: Merge branch parameters by simple averaging to form the next student initialization.

We detail the setup and these steps below. An overview of the approach is illustrated in Figure 2.

3.1 Initialization

Data. Let $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^N$ be a set of problems x with reference answers y . We consider K teacher models $\{\tau_k\}_{k=1}^K$. For each input x , teacher τ_k produces a rationale $r^{(k)}$ and a final answer $\hat{y}^{(k)}$. When y is available, we optionally retain only the teacher outputs that match the reference answer, yielding teacher-specific datasets:

$$\mathcal{D}^{(k)} = \{(x_i, r_i^{(k)}, y_i)\}_{i=1}^{N_k},$$

which filters out teacher trajectories that do not reach the correct final answer.

Model. Let m denote the student with parameters θ . We initialize from the base model parameters $\theta^{(0)}$ and iterate the MoT procedure for $t = 1, \dots, T$ rounds.

3.2 Teacher-Specific SFT (Branch Training)

Targets. For each teacher k , we train the student to produce the teacher’s rationale:

$$\text{target}(x; k) = r^{(k)}.$$

This choice encourages the student to internalize teacher-specific reasoning patterns, rather than only the short final answer.

Objective. The SFT objective for teacher k is the token-level cross-entropy over the target sequence:

$$\mathcal{L}_{\text{SFT}}^{(k)}(\theta) = \mathbb{E}_{(x, r^{(k)}, y) \sim \mathcal{D}^{(k)}} \sum_{t=1}^{L(x, k)} -\log p_{\theta}(z_t \mid x, z_{<t}), \quad (1)$$

where $z_{1:L(x, k)}$ tokenizes $\text{target}(x; k)$. In round t , we initialize K branches from the current merged model and fine-tune each branch on its teacher’s data:

$$\theta^{(t, k)} \leftarrow \arg \min_{\theta} \mathcal{L}_{\text{SFT}}^{(k)}(\theta) \quad \text{with init } \theta^{(t-1)}.$$

3.3 Weight-Space Merging and Iteration

After branch training, we merge the K branch parameters by simple averaging to obtain the next initialization:

$$\theta^{(t)} = \frac{1}{K} \sum_{k=1}^K \theta^{(t,k)}. \quad (2)$$

This step consolidates reasoning features that are shared across branches while smoothing out teacher-specific idiosyncrasies. We repeat the two steps—branch training and weight merge—for T rounds, resulting in the final merged model $\theta^{(T)}$. We aim to leverage *model merging* to overcome conflicts among various teachers’ supervision and, through continuous merge-and-training iterations, unify different teachers’ reasoning abilities and ultimately converge to a consensus reasoning landscape.

4 Experiments Setup

4.1 Datasets

We work in a one-question–multiple-answers (1Q–multiA) setting. We use two high-quality open-source mathematical datasets (BOBA inclusionAI [2025] and S1K Muennighoff et al. [2025]) as our source datasets. From each source dataset, we sample 200 prompts and denote the resulting subsets as BOBA-200 and S1K-200. For every prompt, we query four teacher models—QWEN3-32B Yang et al. [2025a], QWQ Team [2024], DEEPSEEK-R1 Guo et al. [2025], and QWEN3-235B Yang et al. [2025a]. Each teacher generates 16 responses with temperature set to 0.6 and max_tokens set to 32,768. For distillation, we randomly select one correct reasoning path among the 16 as the training label; if none of the 16 responses is correct, we discard that prompt for the corresponding teacher’s distillation corpus.

We construct two training regimes:

1. **Single-Teacher Distillation (STD)**, where we build one distilled corpus per teacher.
2. **Multi-Teacher Distillation (MTD)**, where we aggregate all available distilled samples from all teachers for each source.

The resulting STD and MTD datasets and their sizes are summarized in Table 10. Rows with a specific teacher correspond to STD, while rows with “ALL TEACHERS” correspond to MTD.

4.2 Training Configuration

We fine-tune QWEN3-8B, QWEN3-14B, and QWEN3-30-A3B Yang et al. [2025a] as base models across all experiments. We use a initial learning rate of 1e-5 and a global training batch size of 64. We evaluate the capabilities of the model in mathematical reasoning using AIME24 Math-AI [2024] and AIME25 Math-AI [2025].

For MOT, the base model alternates training on each of the four STD corpora for 50 steps and then performs a merge; this constitutes one merge round. We run 5 merge rounds in total and report the best-performing round as the final MOT result; For STD and MTD baselines, to ensure fairness, we train for 250 steps in total and save a checkpoint every 50 steps. We also report the best-performing checkpoint as the final result. More details are provided in the Appendix C.

5 Multi-teacher distillation and MOT yield substantial gains

Main results. Table 1 reports the final results of MOT on BOBA-200 and S1K-200. For example, “QWEN3-8B+BOBA-200” denotes QWEN3-8B trained with MOT on BOBA-200 dataset. As shown, **with only 200 training examples** from either BOBA-200 or S1K-200, MOT lifts QWEN3-8B to match the baseline performance of QWEN3-14B. Moreover, MOT on QWEN3-14B surpasses strong models including **DEEPSEEK-R1, QWEN3-30B, QWEN3-32B, and OPENAI-O1**, demonstrating substantial gains. All AIME scores are 16-run averages.

Table 1: Main results with MOT on BOBA-200 and S1K-200. AIME scores are 16-run averages; AVG is the mean of AIME24 and AIME25. The last column reports AVG gain vs. the base model.

Configuration	AIME24	AIME25	AVG	AVG Gain
QWEN3-8B	75.83	67.08	71.46	-
QWEN3-8B + BOBA-200 (MOT)	78.33	70.63	74.48	↑3.02
QWEN3-8B + S1K-200 (MOT)	77.50	71.67	74.59	↑3.13
QWEN3-14B	79.17	70.00	74.59	-
QWEN3-14B + BOBA-200 (MOT)	79.38	76.88	78.13	↑3.54
QWEN3-14B + S1K-200 (MOT)	81.67	75.63	78.65	↑4.06
QWEN3-30B-A3B	80.63	70.90	75.77	-
QWEN3-30B-A3B + S1K-200 (MOT)	80.83	77.50	79.17	↑3.40
QWEN3-30B-A3B + BOBA-200 (MOT)	82.92	78.33	80.63	↑4.86
QWEN3-32B	81.46	72.08	76.77	-
DEEPSEEK-R1	79.80	70.00	74.90	-
OPENAI-O1	74.30	79.20	76.75	-
OPENAI-O3-MINI	79.60	74.80	77.20	-

5.1 Ablations: validating STD/MTD and MOT

5.1.1 Comprehensive Ablations of STD, MTD, and MOT

To validate the effectiveness of MOT and multi-teacher distillation, we conduct fine-grained ablations:

- STD: train on each single-teacher distilled dataset (QWQ, QWEN3-32B, QWEN3-235B, DEEPSEEK-R1).
- MTD: train on the union of all teachers’ distilled samples.
- MOT: our method that alternates across the four STD corpora with periodic merges.

For fairness, all methods save a checkpoint every 50 steps, and we report the best checkpoint; full per-step results are provided in the Appendix C.2 and Appendix C.3. Results are shown in Table 2.

Key findings:

- (1) MOT consistently yields the strongest distillation gains in almost all settings. This means that MOT is always superior to the optimal result of the teacher selection method under each setting.
- (2) MTD has more significant distillation yield than the best STD at an 8B scale. However, at a 30B scale, the distillation yield of MTD is actually lower than that of multiple STDs.
- (3) As the scale of the student model grows, the training benefits brought by MTD compared to STD decrease. We guess that as **the scales** of the student model and the teacher model become increasingly close, the student model is more susceptible to the influence of teachers with closer distributions, thereby collapse MTD into Best STD. At this point, the noise from other teachers is amplified. This may makes the effect of MTD even lower than that of STD. **However, the method based on MOT can always learn beneficial information from other teacher models, overcome the noise of directly distilling multiple teacher models, and maintain the optimal distillation result.**

5.1.2 Training Dynamics: MOT vs. Best STD

Finally, we compare QWEN3-8B on the BOBA dataset under MOT and under STD with the best single teacher (QWQ). To isolate optimization dynamics, we log training loss on the same QWQ-distilled corpus every step and evaluate AIME every 50 steps (as in our ablation protocol).

Observations from Figure 3:

Table 2: Ablation on STD, MTD, and MOT across bases and datasets. AIME scores are 16-run averages; AVG is the mean of AIME24 and AIME25.

Dataset	Method	QWEN3-8B			QWEN3-14B			QWEN3-30B-A3B		
		AIME24	AIME25	AVG	AIME24	AIME25	AVG	AIME24	AIME25	AVG
BOBA	Baseline	75.83	67.08	71.46	79.17	70.00	74.59	80.63	70.90	75.77
	MTD (ALL TEACHERS)	76.04	68.96	72.50	76.46	75.42	75.94	79.38	73.96	76.67
	STD (QWQ)	76.25	67.50	71.88	79.58	73.54	76.56	79.79	75.63	77.71
	STD (QWEN3-32B)	75.42	67.71	71.57	77.71	71.25	74.48	81.04	76.04	78.54
	STD (QWEN3-235B)	74.58	67.92	71.25	79.17	74.79	76.98	81.88	75.42	78.65
	STD (DEEPSEEK-R1)	67.71	60.21	63.96	74.38	67.50	70.94	78.33	68.96	73.65
	MOT (ours)	78.33	70.63	74.48	79.38	76.88	78.13	82.92	78.33	80.63
S1K	Baseline	75.83	67.08	71.46	79.17	70.00	74.59	80.63	70.90	75.77
	MTD (ALL TEACHERS)	75.63	70.83	73.23	79.17	73.34	76.26	78.33	74.58	76.46
	STD (QWQ)	76.04	68.13	72.09	80.21	72.92	76.57	81.46	72.92	77.19
	STD (QWEN3-32B)	77.50	66.67	72.09	79.79	72.50	76.15	79.58	73.13	76.36
	STD (QWEN3-235B)	74.38	68.54	71.46	77.08	75.41	76.25	79.17	76.04	77.61
	STD (DEEPSEEK-R1)	70.00	61.46	65.73	73.75	62.92	68.34	78.54	70.63	74.59
	MOT (ours)	77.50	71.67	74.59	81.67	75.63	78.65	80.83	77.50	79.17

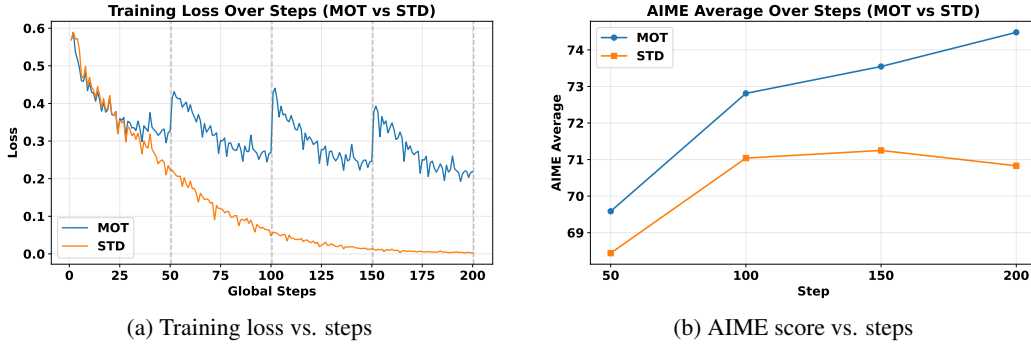


Figure 3: QWEN3-8B on BOBA (QWQ teacher data). Left: training loss vs. steps; right: AIME score vs. steps. We compare MOT and STD (QWQ).

1. MOT achieves substantially higher AIME scores even when its training loss remains much higher than STD’s at the same step. This suggests that in long CoT training, lower loss is not necessarily correlated with stronger reasoning ability.
2. MOT exhibits a higher performance ceiling: its AIME curve achieves a higher peak and sustains strong performance for longer.
3. MOT effectively suppresses overfitting: while STD’s AIME often peaks early and then degrades as training proceeds, MOT maintains stable or improving performances as steps increase.

5.2 MOT mitigates catastrophic forgetting and strengthens general reasoning

To assess whether CoT-style training with MOT affects basic capabilities, we evaluate the final checkpoints trained by MOT and by STD with the per-setting best teacher (Best STD) against the Base models on nine benchmarks: CEVAL (CEV) Seifert et al. [2024], SUPER_GPQA (SG) Du et al. [2025], SIMPLE_QA (SQ) Wei et al. [2024], IFEVAL (IFE) Zhou et al. [2023], MMLU_PRO (MP) Wang et al. [2024], MMLU_REDUX (MR) Gema et al. [2025], PhyBench (PB) Meng et al. [2024], LiveCodeBench (LCB) Jain et al. [2024], and GPQA-Diamond (GPQA-D) Rein et al. [2024]. We group these benchmarks into three categories:

- **catastrophic-forgetting-sensitive tasks** (CEVAL (CEV), SUPER_GPQA (SG), IFEVAL (IFE)).
- **reasoning-related tasks** (SIMPLE_QA (SQ), MMLU_PRO (MP), MMLU_REDUX (MR)).
- **pure reasoning tasks** (PhyBench (PB), LiveCodeBench (LCB), GPQA-Diamond (GPQA-D)).

For each configuration, we report raw scores and summarize the average change versus the Base model within each group: “Avg drop (cat.)” for catastrophic-forgetting tasks and “Avg gain (reason.)” for reasoning-related tasks. We report the results in Table 3 and Table 4.

Key observations:

- Across foundational tasks, long CoT training can either increase or decrease scores. The improvements arise when a benchmark emphasizes general reasoning skills enhanced by training, whereas decreases stem from catastrophic forgetting of factual/knowledge components.
- Compared with training on the single best teacher, MOT typically yields larger gains on reasoning-related and pure reasoning tasks while incurring smaller declines on catastrophic-forgetting-sensitive tasks. This suggests that MOT not only **strengthens general reasoning** but also helps **mitigate catastrophic forgetting**.

Table 3: Impact of Best STD and MOT on general benchmarks, compared to the Base base. Left: catastrophic-forgetting-sensitive tasks; right: reasoning-related tasks. “Avg drop (cat.)” and “Avg gain (reason.)” are average changes vs. Base within each group (negative indicates a drop).

Dataset	Base model	Config	Catastrophic-forgetting-sensitive tasks				Reasoning-related tasks			
			CEV	SG	IFE	Avg drop	SQ	MP	MR	Avg gain
BOBA	QWEN3-8B	Base	83.58	10.51	83.60	-	32.31	71.42	83.21	-
		Best STD	83.43	9.97	81.62	↓-0.89	33.88	72.00	83.68	↑0.87
		MOT	83.73	10.09	82.04	↓-0.61	34.44	73.30	84.42	↑1.74
S1K	QWEN3-8B	Base	83.58	10.51	83.60	-	32.31	71.42	83.21	-
		Best STD	83.95	10.18	82.35	↓-0.40	32.75	72.24	85.02	↑1.02
		MOT	84.32	10.15	83.51	↑0.10	33.56	73.01	84.95	↑1.53
BOBA	QWEN3-14B	Base	86.78	10.76	84.69	-	32.61	75.26	85.74	-
		Best STD	83.73	10.26	82.56	↓-1.89	32.17	74.71	86.37	↓-0.12
		MOT	86.70	10.38	83.51	↓-0.55	32.65	75.59	86.53	↑0.39
S1K	QWEN3-14B	Base	86.78	10.76	84.69	-	32.61	75.26	85.74	-
		Best STD	84.25	10.00	84.32	↓-1.22	32.49	76.21	86.47	↑0.52
		MOT	85.66	10.45	84.42	↓-0.57	32.56	76.55	86.68	↑0.73
BOBA	QWEN3-30B-A3B	Base	85.88	10.66	83.76	-	31.68	75.26	85.81	-
		Best STD	84.18	10.02	80.44	↓-1.89	31.52	75.96	86.04	↑0.26
		MOT	86.55	10.52	83.54	↑0.10	32.26	76.21	86.74	↑0.82
S1K	QWEN3-30B-A3B	Base	85.88	10.66	83.76	-	31.68	75.26	85.81	-
		Best STD	84.62	10.04	79.74	↓-1.97	32.40	75.49	86.67	↑0.60
		MOT	86.48	10.14	82.91	↓-0.26	33.19	76.49	87.28	↑1.40

Table 4: Pure reasoning tasks (PhyBench (PB), LiveCodeBench (LCB), GPQA-Diamond (GPQA-D)) under BOBA-200 and S1K-200. “Avg gain” is the average change vs. Base within each setting (positive indicates an increase).

Base model	Config	BOBA-200				S1K-200			
		PB	LCB	GPQA-D	Avg gain	PB	LCB	GPQA-D	Avg gain
QWEN3-8B	Base	20.47	55.76	57.77	-	20.47	55.76	57.77	-
	Best STD	22.85	59.88	59.85	↑2.86	22.76	59.47	56.31	↑1.51
	MOT	24.07	58.79	60.54	↑3.13	23.37	59.58	59.53	↑2.83
QWEN3-14B	Base	28.53	61.41	60.83	-	28.53	61.41	60.83	-
	Best STD	30.61	63.21	63.79	↑2.28	30.41	63.10	63.70	↑2.15
	MOT	30.77	63.59	64.26	↑2.62	30.78	64.15	64.11	↑2.76
QWEN3-30B	Base	28.57	61.08	59.76	-	28.57	61.08	59.76	-
	Best STD	33.31	61.34	61.81	↑2.35	33.38	63.96	61.46	↑3.13
	MOT	33.46	62.54	62.34	↑2.98	33.40	63.92	62.53	↑3.48

6 MoT enables Selection-Free CoT Distillation

6.1 MOT reliably exploits the best teacher signal

Table 5 summarizes, from the ablations, which single-teacher distillation (STD) source achieves the best distillation performance for each base model and dataset. We observe that different students have different best teacher, and **even for the same student the best teacher can vary across datasets**. In contrast, MOT is consistently strong across settings, matching or surpassing the best single-teacher choice without manual selection.

Table 5: Best teacher under STD for each base model and dataset.

Base model	Best teacher on BOBA-200 (STD)	Best teacher on S1K-200 (STD)
QWEN3-8B	QWQ	QWQ
QWEN3-14B	QWEN3-235B	QWQ
QWEN3-30B-A3B	QWEN3-235B	QWEN3-235B

6.2 MOT distills effectively from a distribution-shifted teacher

6.2.1 Distribution-Shifted Teacher under STD: Quantifying Degradation

Using DEEPSEEK-R1 as the sole teacher (STD) induces notable performance drops for QWEN bases, indicating a strong distribution shift. Table 6 reports the average (AVG) changes relative to the corresponding vanilla baselines; negative values denote degradation.

Table 6: STD with DEEPSEEK-R1 as the teacher leads to AVG drops (relative to vanilla) under BOBA-200 and S1K-200.

Base model	BOBA-200 (AVG change)	S1K-200 (AVG change)
QWEN3-8B	-7.50	-5.73
QWEN3-14B	-3.65	-6.25
QWEN3-30B-A3B	-3.44	-2.50

6.2.2 Ablating a Distribution-Shifted Teacher from MOT: Evidence of Complementarity

To verify that MOT can still leverage useful signals from R1 despite the shift, we ablate R1 from the MOT teacher pool and keep all other settings identical. As shown in Table 7, removing R1 reduces the final MOT performance on BOBA-200 (negative changes), implying that including R1 provides complementary, beneficial supervision that MOT can harness. This proves that MOT can overcome the **performance degradation** caused by the strong distribution shift teacher and extract **beneficial common reasoning features** from it. More details are provided in the Appendix C.4.

Table 7: Impact of removing DEEPSEEK-R1 from the MOT teacher pool on BOBA-200. Negative values indicate a decrease in AVG.

Base model	AVG change
QWEN3-8B	-0.62
QWEN3-14B	-0.21
QWEN3-30B-A3B	-0.42

6.2.3 Optimization Dynamics with/without the Distribution-Shifted Teacher

We further visualize the optimization dynamics for QWEN3-8B on the BOBA dataset under standard MOT and MOT without the R1 teacher. To isolate optimization dynamics, we log training loss every step on the same QWQ-distilled corpus and evaluate AIME every 50 steps (as in our ablation protocol).

Observations from Figure 4:

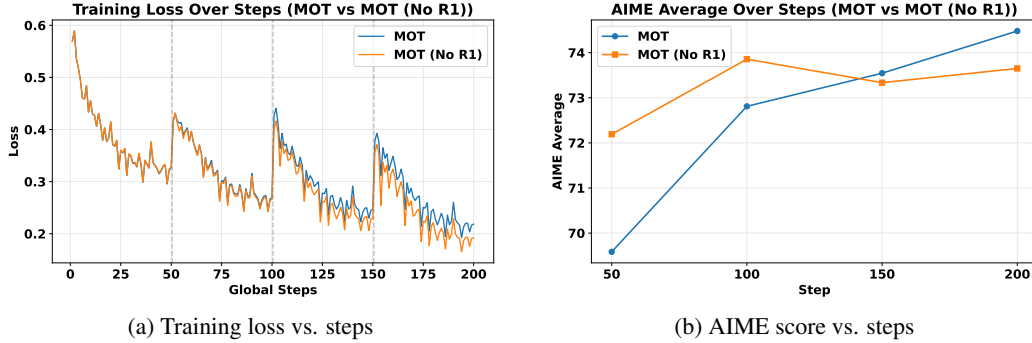


Figure 4: QWEN3-8B on BOBA: standard MOT vs. MOT without R1 in the teacher pool. Left: training loss vs. steps; right: AIME score vs. steps. Both methods use the same QWQ-distilled corpus; AIME is evaluated every 50 steps.

- Including R1 raises the performance ceiling: the AIME curve with R1 continues to improve and reaches a higher peak than the no-R1 variant.
- In the late stage of training, MOT including R1 achieves the global highest AIME while maintaining a higher training loss than the variant without R1 at the same steps.
- Including R1 alleviates overfitting: the no-R1 variant tends to saturate earlier and shows signs of degradation thereafter, whereas MOT with R1 sustains or improves AIME despite a higher training loss, suggesting better regularization and a higher training upper bound.
- This once again proves that MOT can overcome the **performance degradation** caused by the strong distribution shift teacher and extract **beneficial common reasoning features** from it. More details are provided in the

6.3 Can peer-level models act as teachers?

We find that teacher usefulness is not limited to strictly stronger models. Although QWQ, QWEN3-32B, and QWEN3-30B-A3B have comparable parameter scale and reasoning performance, distilling QWEN3-30B-A3B from peer-level teachers (QWQ or QWEN3-32B) still yields gains. This might imply that what truly benefits the model is not necessarily higher-quality reasoning trajectories, and reasoning trajectories distilled from peer-level teachers can still help. In addition, combining peer-level heterogeneous trajectories with MOT further improves results, and using all teachers performs best. Table 8 reports 16-run AIME averages on BOBA-200 with QWEN3-30B-A3B as the base. More details are provided in the Appendix C.5.

Table 8: Peer-level teachers can still help. Results on BOBA-200 with QWEN3-30B-A3B as the base; AIME scores are 16-run averages, AVG is the mean of AIME24 and AIME25.

Teacher setting	AIME24	AIME25	AVG
Base	80.63	70.00	75.32
STD: only QWQ	79.79	75.63	77.71
STD: only QWEN3-32B	81.04	76.04	78.54
MOT: QWQ + QWEN3-32B	81.04	77.29	79.17
MOT: ALL TEACHERS	82.92	78.33	80.63

Overall, these findings support three key conclusions:

- (1) The strongest model is not always the best teacher for a given student and dataset;
- (2) Reasoning trajectories distilled from peer-level teachers can still help.
- (3) MOT robustly integrates complementary and even distribution-shifted supervision, extracting useful signals while mitigating noise.

7 MOT enables consensus CoT

7.1 Better student is a better teacher

To verify that MOT learns higher-quality and more generalizable chains-of-thought (CoT), we conduct a student-as-teacher experiment. Specifically, we take models trained on BOBA-200 under three regimes (Base, Best STD and MOT) and use each **as a teacher** to re-distill on BOBA-200 for a new student model. As shown in Table 9, when the teacher itself is a student trained with MOT, it almost always provides the **strongest distillation signal**, yielding the best downstream student performance. These results indicate that **consensus CoT emerges naturally with MOT**: the student learns trajectories that are both stronger and more consistent, and when used as a teacher, this consensus supervision **transfers** effectively to new students.

Table 9: Student-as-teacher distillation on BOBA-200. Teachers are the final checkpoints obtained with Base (Original model), Best STD (best teacher per setting), or MOT. We report raw scores on AIME24/25, PhyBench, LiveCodeBench, and GPQA-Diamond.

Teacher model	Student model	Teacher Config	AIME24	AIME25	PhyBench	LiveCodeBench	GPQA-Diamond	AVG
QWEN3-14B	QWEN3-8B	Base	74.17	67.08	23.06	58.98	57.80	56.22
		Best STD	75.21	64.17	23.74	56.74	58.33	55.64
		MOT	75.63	68.96	24.28	58.83	59.22	57.38
QWEN3-30B-A3B	QWEN3-14B	Base (Vanilla)	79.17	68.96	28.31	61.41	61.65	59.90
		Best STD	77.08	71.88	29.40	63.36	61.87	60.72
		MOT	80.00	71.67	29.63	62.99	62.69	61.40

7.2 Reverse-trajectory merge probe: MOT vs. MTD

Setup. We linearly interpolate between the *base* model and the final trained checkpoint and evaluate AIME24 at each interpolation weight to probe the local loss landscape reversely. Given parameters θ_{base} and θ_{ckpt} (from either MTD or our MOT), for $\lambda \in [0, 1]$ we define

$$\theta(\lambda) = \lambda \theta_{\text{base}} + (1 - \lambda) \theta_{\text{ckpt}},$$

and report the AIME24 score across a grid of λ (pass@1, 64-run average).

Findings. Across both BOBA-200 and S1K-200 with the 8B student, MOT produces a **markedly smoother** performance trajectory than MTD as the merge weight varies. The training curve follows a smooth rise to a peak and then a gradual decline. This indicates that MOT trains in a **flatter** region of the loss landscape and **better overcomes conflicts among supervision signals from different teachers**. Put simply, MOT blends teachers to agree on the useful signals, so their quirks matter less and noise is filtered out more effectively than with plain MTD.

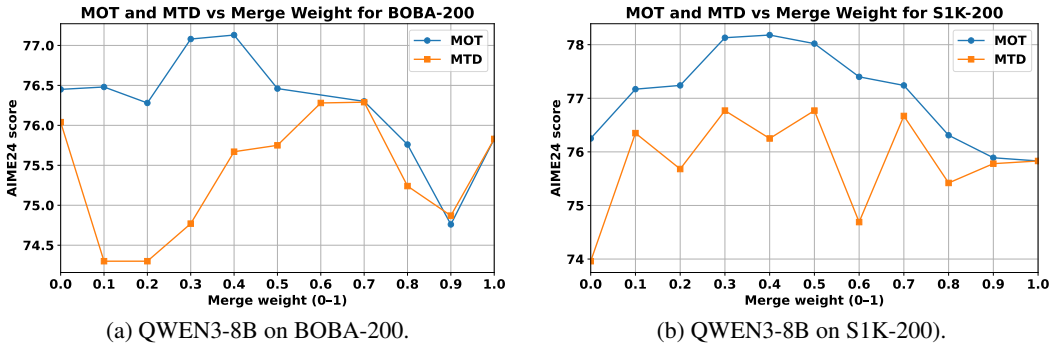


Figure 5: Reverse-merge probe. Interpolating between the base model and an MTD/MOT checkpoint reveals smoother trajectories under MOT, suggesting a flatter loss region and more robust training.

8 Conclusion

We presented *Merge-of-Thought Distillation* (MoT), a lightweight framework that unifies supervision from multiple heterogeneous teachers for long chain-of-thought (CoT) reasoning by alternating

teacher-specific SFT with weight-space merging. Revisiting teacher selection shows that different students have different “best teachers,” and even the same student’s best teacher varies across datasets; MoT sidesteps brittle manual selection by fusing complementary reasoning abilities into a single student. With only about **200** high-quality CoT samples, applying MoT to a **Qwen3-14B** student surpasses **DEEPSEEK-R1**, **QWEN3-30B-A3B**, **QWEN3-32B**, and **OPENAI-O1**. Besides, MoT consistently beats the best single-teacher and naive multi-teacher unions, raises the performance ceiling while mitigating overfitting, and is robust to distribution-shifted and peer-level teachers. Moreover, MOT reduces catastrophic forgetting, improves general reasoning and even cultivates a better teacher—positioning MoT as a simple, scalable route to efficiently distilling long-CoT capabilities into compact students.

References

- Xiao Chen, Sihang Zhou, Ke Liang, Xiaoyu Sun, and Xinwang Liu. Skip-thinking: Chunk-wise chain-of-thought distillation enable smaller language models to reason better and faster. *arXiv preprint arXiv:2505.18642*, 2025a.
- Xinghao Chen, Zhijing Sun, Wenjin Guo, Miaoran Zhang, Yanjun Chen, Yirong Sun, Hui Su, Yijie Pan, Dietrich Klakow, Wenjie Li, et al. Unveiling the key factors for distilling chain-of-thought reasoning. *arXiv preprint arXiv:2502.18001*, 2025b.
- Xinrun Du, Yifan Yao, Kaijing Ma, Bingli Wang, Tianyu Zheng, King Zhu, Minghao Liu, Yiming Liang, Xiaolong Jin, Zhenlin Wei, et al. Supergpqa: Scaling llm evaluation across 285 graduate disciplines. *arXiv preprint arXiv:2502.14739*, 2025.
- Kaituo Feng, Changsheng Li, Xiaolu Zhang, Jun Zhou, Ye Yuan, and Guoren Wang. Keypoint-based progressive chain-of-thought distillation for llms. In *Proceedings of the 41st International Conference on Machine Learning*, pages 13241–13255, 2024.
- Aryo Pradipta Gema, Joshua Ong Jun Leang, Giwon Hong, Alessio Devoto, Alberto Carlo Maria Mancino, Rohit Saxena, Xuanli He, Yu Zhao, Xiaotang Du, Mohammad Reza Ghasemi Madani, et al. Are we done with mmlu? In *Proceedings of the 2025 Conference of the Nations of the Americas Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 5069–5096, 2025.
- Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu, Shirong Ma, Peiyi Wang, Xiao Bi, et al. Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning. *arXiv preprint arXiv:2501.12948*, 2025.
- inclusionAI. Areal-boba-data. <https://huggingface.co/datasets/inclusionAI/AReaL-boba-Data>, 2025. URL <https://huggingface.co/datasets/inclusionAI/AReaL-boba-Data>.
- Aaron Jaech, Adam Kalai, Adam Lerer, Adam Richardson, Ahmed El-Kishky, Aiden Low, Alec Helyar, Aleksander Madry, Alex Beutel, Alex Carney, et al. Openai o1 system card. *arXiv preprint arXiv:2412.16720*, 2024.
- Naman Jain, King Han, Alex Gu, Wen-Ding Li, Fanjia Yan, Tianjun Zhang, Sida Wang, Armando Solar-Lezama, Koushik Sen, and Ion Stoica. Livecodebench: Holistic and contamination free evaluation of large language models for code. *arXiv preprint arXiv:2403.07974*, 2024.
- Xisen Jin, Xiang Ren, Daniel Preotiuc-Pietro, and Pengxiang Cheng. Dataless knowledge fusion by merging weights of language models. In *The Eleventh International Conference on Learning Representations*.
- Liunian Harold Li, Jack Hessel, Youngjae Yu, Xiang Ren, Kai-Wei Chang, and Yejin Choi. Symbolic chain-of-thought distillation: Small models can also "think" step-by-step. In *The 61st Annual Meeting Of The Association For Computational Linguistics*, 2023.
- Yunshui Li, Yiyuan Ma, Shen Yan, Chaoyi Zhang, Jing Liu, Jianqiao Lu, Ziwen Xu, Mengzhao Chen, Minrui Wang, Shiyi Zhan, et al. Model merging in pre-training of large language models. *arXiv preprint arXiv:2505.12082*, 2025a.
- Zihao Li, Xu Wang, Yuzhe Yang, Ziyu Yao, Haoyi Xiong, and Mengnan Du. Feature extraction and steering for enhanced chain-of-thought reasoning in language models. *arXiv preprint arXiv:2505.15634*, 2025b.
- Renjie Luo, Jiayi Li, Chen Huang, and Wei Lu. Through the valley: Path to effective long cot training for small language models. *arXiv preprint arXiv:2506.07712*, 2025a.
- Yijia Luo, Yulin Song, Xingyao Zhang, Jiaheng Liu, Weixun Wang, GengRu Chen, Wenbo Su, and Bo Zheng. Deconstructing long chain-of-thought: A structured reasoning optimization framework for long cot distillation. *arXiv preprint arXiv:2503.16385*, 2025b.

- Junyu Ma, Tianqing Fang, Zhisong Zhang, Hongming Zhang, Haitao Mi, and Dong Yu. Recall with reasoning: Chain-of-thought distillation for mamba’s long-context memory and extrapolation. *arXiv preprint arXiv:2505.03320*, 2025.
- Math-AI. Aime 2024. <https://huggingface.co/datasets/math-ai/aime24>, 2024. URL <https://huggingface.co/datasets/math-ai/aime24>.
- Math-AI. Aime 2025. <https://huggingface.co/datasets/math-ai/aime25>, 2025.
- Fanqing Meng, Wenqi Shao, Lixin Luo, Yahong Wang, Yiran Chen, Quanfeng Lu, Yue Yang, Tianshuo Yang, Kaipeng Zhang, Yu Qiao, et al. Phybench: A physical commonsense benchmark for evaluating text-to-image models. *arXiv preprint arXiv:2406.11802*, 2024.
- Niklas Muennighoff, Zitong Yang, Weijia Shi, Xiang Lisa Li, Li Fei-Fei, Hannaneh Hajishirzi, Luke Zettlemoyer, Percy Liang, Emmanuel Candès, and Tatsunori Hashimoto. sl: Simple test-time scaling. *arXiv preprint arXiv:2501.19393*, 2025.
- Amin Heyrani Nobari, Kaveh Alimohammadi, Ali ArjomandBigdeli, Akash Srivastava, Faez Ahmed, and Navid Azizan. Activation-informed merging of large language models. *arXiv preprint arXiv:2502.02421*, 2025.
- Bo Pang, Hanze Dong, Jiacheng Xu, Silvio Savarese, Yingbo Zhou, and Caiming Xiong. Bolt: Bootstrap long chain-of-thought in language models without distillation. *arXiv preprint arXiv:2502.03860*, 2025.
- Zeyu Qin, Qingxiu Dong, Xingxing Zhang, Li Dong, Xiaolong Huang, Ziyi Yang, Mahmoud Khademi, Dongdong Zhang, Hany Hassan Awadalla, Yi R Fung, et al. Scaling laws of synthetic data for language models. *arXiv preprint arXiv:2503.19551*, 2025.
- David Rein, Betty Li Hou, Asa Cooper Stickland, Jackson Petty, Richard Yuanzhe Pang, Julien Dirani, Julian Michael, and Samuel R Bowman. Gpqa: A graduate-level google-proof q&a benchmark. In *First Conference on Language Modeling*, 2024.
- Christin Seifert, Jörg Schlötterer, et al. Ceval: A benchmark for evaluating counterfactual text generation. In *Proceedings of the 17th International Natural Language Generation Conference*, pages 55–69, 2024.
- Yudi Shi, Shangzhe Di, Qirui Chen, and Weidi Xie. Enhancing video-llm reasoning via agent-of-thoughts distillation. *arXiv preprint arXiv:2412.01694*, 2024.
- Derek Tam, Margaret Li, Prateek Yadav, Rickard Brühl Gabrielsson, Jiacheng Zhu, Kristjan Greenewald, Mikhail Yurochkin, Mohit Bansal, Colin Raffel, and Leshem Choshen. Llm merging: Building llms efficiently through merging. In *NeurIPS 2024 Competition Track*, 2024.
- Qwen Team. Qwq: Reflect deeply on the boundaries of the unknown. *Hugging Face*, 2024.
- Yubo Wang, Xueguang Ma, Ge Zhang, Yuansheng Ni, Abhuranil Chandra, Shiguang Guo, Weiming Ren, Aaran Arulraj, Xuan He, Ziyang Jiang, et al. Mmlu-pro: A more robust and challenging multi-task language understanding benchmark. *Advances in Neural Information Processing Systems*, 37: 95266–95290, 2024.
- Jason Wei, Nguyen Karina, Hyung Won Chung, Yunxin Joy Jiao, Spencer Papay, Amelia Glaese, John Schulman, and William Fedus. Measuring short-form factuality in large language models. *arXiv preprint arXiv:2411.04368*, 2024.
- Han Wu, Yuxuan Yao, Shuqi Liu, Zehua Liu, Xiaojin Fu, Xiongwei Han, Xing Li, Hui-Ling Zhen, Tao Zhong, and Mingxuan Yuan. Unlocking efficient long-to-short llm reasoning with model merging. *arXiv preprint arXiv:2503.20641*, 2025a.
- Xiaojun Wu, Xiaoguang Jiang, Huiyang Li, Jucai Zhai, Dengfeng Liu, Qiaobo Hao, Huang Liu, Zhiguo Yang, Ji Xie, Ninglun Gu, et al. Beyond scaling law: A data-efficient distillation framework for reasoning. *arXiv preprint arXiv:2508.09883*, 2025b.

- Prateek Yadav, Tu Vu, Jonathan Lai, Alexandra Chronopoulou, Manaal Faruqui, Mohit Bansal, and Tsendsuren Munkhdalai. What matters for model merging at scale? *arXiv preprint arXiv:2410.03617*, 2024.
- An Yang, Anfeng Li, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chang Gao, Chengen Huang, Chenxu Lv, et al. Qwen3 technical report. *arXiv preprint arXiv:2505.09388*, 2025a.
- Enneng Yang, Li Shen, Guibing Guo, Xingwei Wang, Xiaochun Cao, Jie Zhang, and Dacheng Tao. Model merging in llms, mllms, and beyond: Methods, theories, applications and opportunities. *arXiv preprint arXiv:2408.07666*, 2024.
- Jinluan Yang, Dingnan Jin, Anke Tang, Li Shen, Didi Zhu, Zhengyu Chen, Ziyu Zhao, Daixin Wang, Qing Cui, Zhiqiang Zhang, et al. Mix data or merge models? balancing the helpfulness, honesty, and harmlessness of large language model via model merging. *arXiv preprint arXiv:2502.06876*, 2025b.
- Yixin Ye, Zhen Huang, Yang Xiao, Ethan Chern, Shijie Xia, and Pengfei Liu. Limo: Less is more for reasoning. *arXiv preprint arXiv:2502.03387*, 2025.
- Le Yu, Bowen Yu, Haiyang Yu, Fei Huang, and Yongbin Li. Extend model merging from fine-tuned to pre-trained large language models via weight disentanglement. *arXiv preprint arXiv:2408.03092*, 2024a.
- Le Yu, Bowen Yu, Haiyang Yu, Fei Huang, and Yongbin Li. Language models are super mario: Absorbing abilities from homologous models as a free lunch. In *Forty-first International Conference on Machine Learning*, 2024b.
- Ruiqi Zhang, Changyi Xiao, and Yixin Cao. Long or short cot? investigating instance-level switch of large reasoning models. *arXiv preprint arXiv:2506.04182*, 2025.
- Yiming Zhang, Baoyi He, Shengyu Zhang, Yuhao Fu, Qi Zhou, Zhijie Sang, Zijin Hong, Kejing Yang, Wenjun Wang, Jianbo Yuan, et al. Unconstrained model merging for enhanced llm reasoning. *arXiv preprint arXiv:2410.13699*, 2024.
- Jeffrey Zhou, Tianjian Lu, Swaroop Mishra, Siddhartha Brahma, Sujoy Basu, Yi Luan, Denny Zhou, and Le Hou. Instruction-following evaluation for large language models. *arXiv preprint arXiv:2311.07911*, 2023.
- Yuyan Zhou, Liang Song, Bingning Wang, and Weipeng Chen. Metagpt: Merging large language models using model exclusive task arithmetic. *arXiv preprint arXiv:2406.11385*, 2024.

A Limitations

- (1) We currently merge branches via simple uniform parameter averaging; future work will explore alternative merge strategies.
- (2) Beyond AIME24/25, there is a lack of sufficiently challenging math benchmarks, which limits evaluation depth on high-difficulty mathematical reasoning.

B Dataset

Table 10: STD and MTD distillation datasets derived from BOBA-200 and S1K-200.

Source	Teacher	Distillation dataset name	Size
BOBA-200	QWQ	BOBA-200-QWQ	195
	QWEN3-32B	BOBA-200-32B	191
	QWEN3-235B	BOBA-200-235B	197
	DEEPSEEK-R1	BOBA-200-R1	198
	ALL TEACHERS	BOBA-200-MTD	781
S1K-200	QWQ	S1K-200-QWQ	161
	QWEN3-32B	S1K-200-32B	164
	QWEN3-235B	S1K-200-235B	169
	DEEPSEEK-R1	S1K-200-R1	168
	ALL TEACHERS	S1K-200-MTD	662

C Additional training details and full ablations

C.1 Training hyperparameters

Unless otherwise noted, all experiments follow a shared set of training choices designed for long chain-of-thought (CoT) sequences and stable optimization:

- Model/input formatting: We use the Qwen3 instruction template to format prompts and responses consistently across datasets.
- Context length: The maximum sequence length is 25k tokens to accommodate long CoT traces with minimal truncation.
- Precision and kernels: Training uses bfloat16 (bf16) with FlashAttention-2 to improve memory efficiency and throughput for long contexts.
- Optimizer and schedule: AdamW with betas (0.9, 0.95), weight decay 0.1, cosine learning-rate schedule with a base learning rate of 1e-5 and 1% warmup. Gradients are clipped at a norm of 1.0 for stability.
- Batch and accumulation: We train on $8 \times$ H800 GPUs with a per-device batch size of 1 and gradient accumulation of 8, resulting in an effective batch size of 64 sequences per optimization step.
- Logging and checkpointing: We log every step and save a checkpoint every 50 steps; up to 10 most recent checkpoints are kept, and only model weights are saved to reduce I/O overhead.

Protocol-specific details:

- MOT: One “round” consists of 50 optimization steps on a given teacher corpus before merging; we run five rounds and evaluate after each merge.
- STD/MTD: We train for 250 steps and save/evaluate checkpoints every 50 steps; the best checkpoint is reported in the main text.

Table 11: Complete ablations on AIME 2024 (A24) and AIME 2025 (A25). Each entry is a 16-run average. We report per-checkpoint results for STD/MTD (every 50 steps, up to 250), and per-round results for MOT (Rounds 1–5).

Method	Config	BOBA-200						S1K-200					
		QWEN3-8B		QWEN3-14B		QWEN3-30B-A3B		QWEN3-8B		QWEN3-14B		QWEN3-30B-A3B	
		A24	A25	A24	A25	A24	A25	A24	A25	A24	A25	A24	A25
Base model	(40k)	75.83	67.08	79.17	70.00	81.67	72.50	75.83	67.08	79.17	70.00	81.67	72.50
STD (QWEN3-32B)	STEP 50	75.42	67.71	77.71	71.25	81.04	76.04	77.50	66.67	79.79	72.50	79.58	73.13
	STEP 100	74.17	65.83	77.71	68.13	80.83	72.50	74.58	68.96	77.71	70.21	79.58	70.63
	STEP 150	75.41	63.96	78.13	66.04	81.88	72.92	73.75	67.71	79.58	72.08	80.63	70.42
	STEP 200	74.58	63.75	76.67	66.88	80.63	75.63	75.21	66.67	79.79	69.58	79.58	70.83
	STEP 250	73.96	62.92	77.50	70.21	79.38	69.79	76.04	66.04	77.29	70.63	79.17	70.00
STD (QWEN3-235B)	STEP 50	74.58	67.92	78.13	74.79	80.00	78.13	74.38	68.54	77.92	72.71	77.92	75.63
	STEP 100	73.13	68.33	79.17	74.79	81.88	75.42	72.50	65.83	77.08	75.41	77.08	76.88
	STEP 150	71.88	66.67	78.13	70.42	77.92	76.04	74.17	67.71	77.71	72.08	78.54	74.58
	STEP 200	71.04	65.83	77.29	74.17	79.58	75.83	71.46	67.29	78.75	73.13	78.33	74.58
	STEP 250	75.00	67.29	79.38	74.17	80.42	73.54	73.96	67.08	76.67	71.46	79.17	76.04
STD (QWQ)	STEP 50	72.50	64.38	76.46	68.54	79.58	72.50	73.53	69.17	79.17	73.54	80.83	72.08
	STEP 100	75.00	67.08	78.33	73.33	78.54	76.46	76.04	68.13	79.58	71.88	81.46	72.92
	STEP 150	75.21	67.29	79.58	73.54	79.79	75.63	75.21	65.42	79.17	73.33	80.63	68.96
	STEP 200	75.83	65.83	77.29	71.46	78.54	73.96	74.58	65.63	80.21	72.92	82.08	70.63
	STEP 250	76.25	67.50	78.54	71.67	78.33	75.83	74.58	64.17	77.92	74.79	81.25	70.83
STD (DEEPSEEK-R1)	STEP 50	67.71	60.21	74.38	67.50	78.33	68.96	70.00	61.46	73.75	62.92	78.54	70.63
	STEP 100	70.21	53.33	73.75	63.33	75.00	69.79	68.54	58.33	73.33	63.13	76.46	64.58
	STEP 150	65.83	56.04	74.58	63.75	74.79	64.38	67.92	52.08	73.96	62.71	75.63	66.04
	STEP 200	65.21	53.75	74.58	64.79	74.58	67.50	66.67	55.83	71.88	61.25	74.17	65.21
	STEP 250	66.67	55.42	72.50	63.54	75.42	66.88	66.88	51.67	72.71	63.96	74.17	70.00
MTD (ALL TEACHERS)	STEP 50	68.54	61.04	74.79	66.88	79.17	72.92	70.83	63.54	75.83	70.83	76.46	72.08
	STEP 100	73.75	66.46	76.88	72.92	79.17	73.75	75.63	70.83	78.75	73.13	77.29	75.42
	STEP 150	71.88	68.64	76.46	75.42	77.92	72.92	73.33	66.88	79.17	73.34	78.33	74.58
	STEP 200	75.00	66.04	79.58	72.50	78.75	73.75	74.17	69.38	77.08	73.33	78.33	74.58
	STEP 250	76.04	68.96	77.29	73.54	79.38	73.96	73.96	69.17	79.79	73.13	79.58	72.71
MOT (ours)	Round 1	72.29	66.88	78.75	73.95	80.63	73.13	74.79	69.17	78.33	69.79	80.00	75.42
	Round 2	75.83	69.79	79.58	73.54	79.79	76.04	77.71	70.63	80.21	74.38	82.29	74.58
	Round 3	76.67	70.42	80.00	74.79	80.00	77.92	76.25	70.00	80.00	74.38	79.79	74.79
	Round 4	78.33	70.63	79.38	76.88	81.25	75.63	77.50	71.67	79.38	75.00	80.83	77.50
	Round 5	76.45	66.88	78.96	73.75	82.92	78.33	76.25	68.13	81.67	75.63	80.00	77.50

C.2 MOT merge schedule (per-round results)

For MOT, we alternate the base model across the four STD corpora (QWQ, QWEN3-32B, QWEN3-235B, DEEPSEEK-R1), training 50 steps on each corpus and then performing a merge; this constitutes one merge round. We run five rounds in total and evaluate after every round. The complete per-round results for all base models and both sources (BOBA-200 and S1K-200) are reported in Table 11.

C.3 STD/MTD per-checkpoint results

For STD and MTD, we train for 250 steps and save a checkpoint every 50 steps; we evaluate each checkpoint and report the best in the main text. Table 11 lists the full per-checkpoint results across all base models and both sources.

Key observations from the ablations:

1. MOT consistently yields the strongest distillation gains in almost all settings.
2. For 8B/14B bases, MTD typically surpasses the best single-teacher STD, indicating beneficial complementarity across teachers.
3. For 30B-A3B, MTD brings little to no gain. We hypothesize that QWQ, QWEN3-32B, and DEEPSEEK-R1 are not clearly stronger than the 30B base, so the union is dominated by QWEN3-235B; in contrast, MOT can glean useful signals from the other teachers while mitigating noise, yielding the best results.

C.4 Detailed MOT (without R1) Results on BOBA-200

Table 12 reports per-round AIME scores for MOT after ablating the DEEPSEEK-R1 teacher (all other settings identical). AVG is computed as the mean of AIME24 and AIME25.

Table 12: MOT without DEEPSEEK-R1 on BOBA-200: per-round AIME24/AIME25 and AVG. $AVG = (AIME24 + AIME25)/2$.

Base model	Round	AIME24	AIME25	AVG
QWEN3-8B	Round 1	75.21	69.17	72.19
	Round 2	75.42	72.29	73.86
	Round 3	76.67	70.00	73.34
	Round 4	78.13	69.17	73.65
	Round 5	76.46	69.79	73.13
QWEN3-14B	Round 1	80.63	72.71	76.67
	Round 2	79.79	74.58	77.19
	Round 3	80.83	74.58	77.71
	Round 4	81.04	74.79	77.92
	Round 5	79.58	74.79	77.19
QWEN3-30B	Round 1	81.88	75.00	78.44
	Round 2	81.88	77.08	79.48
	Round 3	81.25	78.75	80.00
	Round 4	81.88	77.71	79.80
	Round 5	80.42	80.00	80.21

Overall, while MOT without R1 remains competitive, the best AVG per model is consistently below the corresponding full MOT results reported in the main text. This supports the claim that R1 offers complementary supervision that raises the training ceiling and improves late-stage generalization.

C.5 Detailed MOT with peer-level teachers (QWQ + QWEN3-32B) on BOBA-200

Table 13 reports per-round AIME scores for MOT when using only peer-level teachers (QWQ and QWEN3-32B) with QWEN3-30B as the base. AVG is computed as the mean of AIME24 and AIME25.

Table 13: MOT with peer-level teachers (QWQ + QWEN3-32B) on BOBA-200: per-round AIME24/AIME25 and AVG for QWEN3-30B. $AVG = (AIME24 + AIME25)/2$.

Round	AIME24	AIME25	AVG
Round 1	82.70	73.95	78.33
Round 2	80.83	74.58	77.71
Round 3	82.08	75.83	78.96
Round 4	80.83	75.00	77.92
Round 5	81.04	77.29	79.17